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Review of ECG Analysis

In 1887, Augustus D. Waller published the first human electrocardiogram (ECG) recorded with a capillary electrometer. Subsequently, Willem Einthoven invented a more sensitive galvanometer for producing ECG using a fine quartz string coated in silver. He invented the lead system for ECG recording and identified the five deflection points in the cardiac cycle by naming them P, Q, R, S and T which are still being used in the present standards (see Fig. 1.2). Einthoven also started transmission of ECG from hospital to his laboratory on telephone lines [33]. Since then a huge knowledge base has been generated covering clinical and engineering aspects of electrocardiography. Since last few decades electronic recorders have been developed for digital recording of the ECG signal. In recent years the ECG recorders are available in a much compact form so that the user can wear it for ECG recording without much of obstruction in the routine activities. Recently, the wearable ECG recorders (W-ECG) are becoming very popular because of their low cost, long term recording capability and ease of use.

Since a huge volume of ECG data is generated by the W-ECG, automated methods are preferred for analysis of the ECG signal. The ECG data may be composed of single-lead or multiple-lead ECG signals depending upon the type and configuration of the ECG recorder. Accordingly, the method of analysis is also different. Single-lead ECG waveform analysis includes wave shapes (morphologies), spectra and repeatability of the cardiac cycle. On the other hand, multi-lead ECG processing algorithms can utilize additional information like simultaneous features from other leads. This may lead to a greater immunity against interference signals. The disadvantage of multiple leads lie in increased patient discomfort and stress, especially for ambulatory testing. For the purpose of basic cardiac monitoring during ambulatory testing, it is desirable to have fewer leads and hence single-lead algorithms are more suitable for W-ECG applications. In this chapter we will review some of the existing techniques developed for analysis of single-lead ECG signals.

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2.1 QRS Detection Methods

As we have seen in Chapter 1, ECG is a pseudo-periodic signal in the sense that the cardiac cycle repeats according to heart rate. However, the heart rate may not remain constant. The components of cardiac cycles appear in a regular sequence P-QRS-T. The variations in the heart rate may affect the durations of PQ and ST segments while the durations of P wave, QRS complex and T wave may still remain the same for a normal heart. The R peak in the QRS complex is the dominant feature of the cardiac cycle, which can be distinctly recognized from the sharp edges and a high amplitude as we have seen in Fig 1.2. Therefore, it is relatively easy to locate the QRS complex in the ECG even in the presence of low frequency noise (like baseline wandering due to respiration) and hence this is used for determining the current heart beat. The QRS detection forms the basis of most ECG analysis algorithms, particularly those used for arrhythmia monitoring [19, 77, 127]. The current heart rate may be determined by calculating the time period between the two consecutive R peaks. Moreover, specific ECG parameters can be derived using the R peak locations. For example, ST segment is measured at a certain predefined time interval from the end of the QRS complex [121] and the corrected QT interval is derived by well known Bazzet's formula using the current QT and RR intervals [14]. This explains the importance of QRS detection in cardiac monitoring using ECG.

QRS detection algorithms, in general, use the relatively high energy contents of the QRS complex that lie in 5-25Hz band [63, 96, 128]. The more complex QRS detection algorithms involve application of neural network, hidden Markov model (HMM), syntactic methods, etc. [22, 48, 124, 133], but they are rarely used in low cost W-ECG applications. Further details of the QRS detection methods and the comparisons of their performances in presence of noise and their computational complexities can be found in [35, 63, 95]. Most of the simple QRS detection algorithms are based on one of the following methods: derivatives, filter-banks, wavelets, mathematical morphology and correlation [35, 63]. Here a few of the approaches in literature for QRS complex detection are discussed in brief.

The characteristic of higher slopes of the QRS complex inspires one to use temporal derivatives for its detection. In the derivative based methods, the ECG signal is first smoothed with an appropriate moving average filter for suppressing any high frequency noise outside the 5-25Hz band. The smoothed signal is differentiated to emphasize the high slopes and to suppress smooth ECG waves and baseline wanders. The overall response of these two simple arithmetic operations results in a bandpass filter to match the spectral band of the QRS while suppressing the relatively low frequencies in P and T waves. The squared magnitude of the derivative signal is used to enhance further the high derivatives of the QRS complex. A moving average integration filter with the window length matching the duration of QRS complex is applied after the squaring operation. The integrated signal is then searched for the local maxima exceeding an appropriate threshold value. The search is further refined by eliminating the points which occur within the refractory period of a ventricular activity [41, 94, 96].

Wavelet based methods for QRS detection use the principle of singularity detection in the wavelet coefficients [74]. Wavelet coefficients of the ECG signal at several scales are analyzed [11, 59, 70, 71, 111] to find the local maxima and positions of matching in two consecutive scales to locate QRS positions. This is based on the assumption that the energy of the QRS complex is continuously spread over the spectral bands as well as the temporal scales. The noise in the signal may not have this kind of property and hence false alarms due to such noise can be reduced using this multiscale approach.

In a filter bank approach of QRS detection, subbands at different scales are combined to confirm the positions of the local maxima [4]. The filter bank approach is based on the fact that the QRS complex has simultaneous presence in the subbands, whereas other ECG waves and noise may not exhibit this characteristic behavior. This is similar to the wavelet based approach of QRS detection. In [15, 123], a generalized class of filter with a transform having two factors, $(1 - z^{-K})(1 + z^{-1})^L$ is given: the first implements a difference with integer delay K and the other is for a lowpass filter with band width controlled by an integer parameter L. The integer parameters (K, L) are determined depending upon the sampling rate. At a sampling rate of 100Hz, $(K, L) = (1, 2)$ is found to be most suitable choice in [123]. In [25], $(K, L) = (5, 4)$ is used at the sampling rate of 250Hz.

In morphology based QRS detection approach, morphological operators like opening and closing are used to enhance the particular shape of the QRS complex. The QRS complex contains abrupt positive and negative peaks, therefore, using a peak-valley extractor [76], the QRS complexes are enhanced and the other parts of the signal such as P and T waves as well as noise are suppressed [132]. Peak-valley (PV) extractor is a morphological operation used for mapping smooth parts of a signal to corresponding zero amplitude flat segments to extract peaks and valleys in the signal. In PV extractor, a smoothed signal is derived from the opening followed by closing of the input signal by a horizontal structuring element. The structuring element, which is a horizontal line segment of unit amplitude, does not form the basis for the peak and valley and hence, the peaks and valleys of the input signal are mapped to zeros in the smoothed signal. Next, the smoothed signal is subtracted from the input signal itself to yield a PV extracted signal containing only peaks and valleys of the input signal. This approach has previously, been used in [21] for suppression of impulsive noise and baseline correction in ECG signals.

In [146], a curve length transform is used for the detection of QRS complex. The curve length is defined as the sum of distances (Euclidean) between pairs of consecutive sample points in the ECG signal. The curve length of the ECG signal depends on the increments in the sample values and the sampling time of the ECG. For uniform sampling in time the curve length is a measure of the increments in sample values. For QRS detection the curve length of the ECG signal is evaluated in a window with the length matching with the widest possible QRS complex. When the window is in perfect alignment with the onset of QRS complex it produces the local maximum in the curve length feature and that is utilized for locating the onsets of the QRS complex. A lowpass filter with 3dB cut-off at 16Hz is used as a preprocessing step to suppress noise.

In [110], a real time, microprocessor based QRS detection method is given. An analog filter with a pass band of 0.5-35Hz, and automatic gain derived from the signal envelope is used as a pre-processing stage. The signal is digitized at a sampling rate of 500Hz and further processed through a 0.5-40Hz bandpass filter and a 50Hz notch filter for suppressing the baseline wander, high frequency noise and the power line noise. A 128 tap matched filter is derived from a noise free, bandpass filtered QRS complex, which is used for detection of QRS complexes in the ECG signal. We found the method to be suitable for the analysis of ambulatory ECG also.

2.2 Delineation of Wave Boundaries

In the previous section we have reviewed some of the QRS detection techniques in the literature. For automated analysis of the ECG, detections of P and T waves are also important as the P wave represents atrial activity and the T wave is related to repolarization of ventricles. In a cardiac cycle the sequence of occurrence of these waves is P-QRS-T. Therefore, we can search for P and T waves in appropriate time windows after the QRS complex is located. However, it is recommended in [66] that any fibrillation condition should be detected before proceeding with waveform analysis using procedures proposed in [129].

The T wave is the wave with the next highest level of energy in cardiac cycle. The location of T wave from the R peak depends on the current beat period, measured as the time interval between two consecutive R peaks which is simply called RR interval. In [67], the search window for T wave is defined from the R peak position in the interval from 140 to 500ms if mean(RR interval) $>$ 700 ms and for smaller RR intervals the search window is defined in the range 100ms to 0.7*RR interval (in ms). The ECG deflection points Q, R, S and T are located using a lowpass filter from the differentiated ECG. In [78, 79], a quadratic spline wavelet is used at four dyadic scales starting from the scale of 2 at a sampling rate of 250Hz. The first two scales are used for detecting QRS and the next two scales are used for detecting P and T waves in appropriately chosen time windows with respect to the location of R peak in the QRS complex.

In [34], assuming that P wave occurs in a specified time window of 240 to 400ms preceding the R wave of the QRS complex in each cardiac cycle, three different P wave detection algorithms are discussed. These techniques are based on the derivatives of the ECG signal in a specified window. First method in [34] is called the amplitude and first derivative based algorithm. This technique subjects the first derivative of the ECG signal in a specified time window to a predefined threshold value. The criterion applied for P wave detection is: the positive derivative at three consecutive points in the window should exceed the threshold followed by two consecutive points having the negative derivative crossing the threshold within 48ms, and all the sample values in the signal in between these two crossing points must exceed a predefined amplitude threshold. The second technique just searches for a point in the time window at which the negative derivative exceeds the threshold value and in the third method a combination of second derivative and a smoothed first derivative signal is subjected to a threshold value for detection of P wave.

There are model based approaches for analysis of different segments of the cardiac cycle, i.e., P, QRS and T waves. In [55], P, QRS, ST and T are expressed as linear combinations of Hermite functions. This modeling required 2, 7, 2 and 4 Hermite coefficients to represent P, QRS, ST and T, respectively. In [88], a discrete cosine transform based modeling is proposed for delineation of P, QRS and T waves. The biphasic functions given by pole-zero model of order (2,2) are used in this representation. It is shown in [88] that P and T each has a single biphasic function whereas QRS can be represented as two or three biphasic functions. These segmentations of ECG waves are useful for further analysis and compression of ECG signals.

The level and slope of the ST segment are sensitive to levels of physical activity. The ST level is measured with respect to the baseline or isoelectric level of the ECG which can be detected by searching for the flattest line segment between P and Q waves [46, 140]. A method for determining the measurement point for the ST level in terms of current heart rate is given in [46]. In [140], the ST level is measured at $J + 80$ms where J is the first inflection point after the S wave. In order to provide immunity against motion artifacts, the ST levels are measured after taking average from several consecutive beats with similar morphology and perfect alignment. A few methods for ECG beat alignment from the literature are described in the next section.

A different approach of ECG segmentation uses a fixed number of functions where the middle and end points of the functions are matched with the wave shapes in ECG signal [98]. This kind of segmentation is used for recognition of ST segments in [119]. A similar approach using a piecewise linear approximation is given in [135]. Here a line segment is initiated from the start of the cardiac cycle and is extended up to the point for which the error in approximation of the ECG segment is less than a fixed empirical value. A new segment is started from the end point of the previous segment. The advantage of this method is that the cardiac cycle can be described in terms of fewer parameters like slopes and lengths of the line segments.

2.3 Beat Alignment

Certain measurements like levels of ST and T waves and morphology of P-QRS-T complex in the cardiac cycle are important for diagnosis of any abnormality. However, the presence of noise can hamper the readability of the ECG and hence can produce errors in estimating these cardiac parameters. In order to reduce the impact of noise, the cardiac cycle should be derived as an average of several epochs of ECG beats. Such estimates using mean composite, median composite, etc., are presented in [5]. This kind of estimation of the cardiac cycle requires correct alignment of corresponding cardiac features like P, QRS and T waves in the ECG beats.

There are various methods for alignment of ECG beats in the literature namely, the double level method, normalized integral method and matched filtering method, etc. These techniques are reviewed in [56, 58]. In the double level method, crossings of a fixed threshold level by the signal in upward and downward directions are measured as time t_1 and t_2, respectively. The mean of these two, $t_a = (t_1 + t_2)/2$ is used as the temporal point of alignment. In the normalized integral method proposed in [58], a measure called normalized integral of a non-negative function is defined. The integral of a non-negative function is always monotonically increasing and hence it can uniquely represent the time corresponding to a particular amplitude. If we consider a finite delay between two non-negative functions with the same shape and amplitude, then the area under the difference signal between the corresponding integral signals represents the amount of delay. The normalized integral is defined as the running integral divided by the final value of the integral of the function. Therefore, irrespective of the amplitude scales of the function, the normalized integral monotonically increases from 0 to 1 for a non-negative function. Thus, as explained above, the delay can be determined even though the waveforms may have different amplitude scales. The only requirement is that the waveforms should be non-negative to maintain the unique relation of time and amplitude. Since the ECG signal may go below the isoelectric level it may have negative valued samples which are to be replaced by zeros for applying this technique. In the matched filter based technique a noise-free ECG beat forms an impulse response of the matched filter. The local maxima in the output of the matched filter signal indicate positions of the alignment of the beat in the input ECG signal. This is similar to finding cross-correlation of the new beat with the reference beat for their alignment. In [64], a multiscale cross-correlation based approach is proposed for beat alignment. The cross-correlation between a template beat and the current ECG beat is calculated at five different scales and the median of the locations of the maxima, at all the scales is used as the fiducial point for alignment.

In [27], the beat alignment is performed after searching for R peak. The first zero crossing after the R peak is marked as a fiducial point for alignment. Any dc bias and slow baseline wanders are to be removed to ensure that the zero crossing takes place as desired. Therefore, the signal is preprocessed through a highpass filter with a cut-off at 3Hz. Respiration causes a significant beat to beat variation in amplitude of QRS complex. Hence normalization of the QRS amplitudes is used in [114] for minimizing errors in alignment. A multiple loop alignment approach is proposed in [122] using vectorcardiographic leads which is not applicable to ambulatory cardiac monitoring. A similar approach of multiple loop alignment is used in [10] for studying beat to beat variability.

2.4 Noise Reduction in ECG

It has been noted previously that noise from various sources like muscular activities, 50/60Hz powerline, skin stretching and electrode motion, movement of heart due to respiration, etc. can contaminate the ECG signal and hence affect the interpretation of ECG signal. In particular, an automated analysis requires noise free ECG signal for correct interpretation. However, it is difficult to control the environment and prevent the interference due to some physiological events like breathing. Reduction of noise due to most common sources is addressed in [137].

Thakor *et al.* have presented several adaptive filtering approaches in [130] for noise cancellation in ECG signals. An adaptive filter with a single weight has been proposed here for reducing slow wandering of baseline. A constant is used as the reference signal and the composite ECG signal with baseline wandering is the primary input. At every sample of the ECG signal, the error produced by the difference between the constant reference and the filter weight multiplied by the previous input sample (since it is a single weight filter) is used for updating the filter weight according to the least mean squares (LMS) algorithm as $w[n+1] = w[n] + 2\mu e[n]$, where $e[n]$ is error signal, $w[n]$ is the filter weight at n^{th} sample and μ is the adaptation parameter. The output of the filter is the error signal $e[n]$. If we consider the relation between the input ECG and the output error signal, the filter acts as a notch at zero frequency. The transfer function of this filter in s domain can be derived as $\frac{s/(\mu f_s/\pi)}{1+s/(\mu f_s/\pi)}$, where f_s is the sampling frequency. The bandwidth of the notch is given as $(\mu/\pi)f_s$, which should not exceed the fundamental frequency of the heart rate ($\approx$ 0.8Hz) as indicated in [7, 54]. Due to this limit the adaptive filter can track the slow baseline wander but cannot remove abrupt motion artifact signal due to physical movement.

Powerline is another most usual source of interference in the ECG recording. This kind of interference is caused due to powerline cords nearby and its effect can be minimized by moving aways from such sources of this noise. However, there must be provision in the wearable ECG equipment to minimize the interference. As we know that the powerlines have a specific frequency of either 50 or 60Hz. Therefore, the interference can be removed by using a narrow stopband filter centered at the powerline frequency in the frequency response of the ECG equipment, which is usually from 0.05-100Hz. The notch filter for powerline is acceptable by the guidelines provided in [28] for exercise monitoring ECG equipment. In [7], authors proposed a technique for removing the powerline interference using a non-recursive finite impulse response. A design of infinite impulse response notch filter is proposed in [104] which can be useful for filtering of ECG signals. Adaptive filtering techniques are applied for cancellation of powerline and the electromyograph (EMG) interference in [130]. The powerline interference appears as the common mode signal to the ECG amplifier and available from the right leg electrode. Hence the signal from the right leg electrode is used as the reference input signal to the adaptive filter for cancellation of powerline noise. Here it should be noted that in many places the powerline frequency may often deviate from the specified value (either 50 or 60Hz) in the range of $\pm$2Hz. In this case, the adaptive filtering technique can be more effective [69]. Moreover, it has been shown in [39], the adaptive implementation introduces less noise in measurement of the ST segment in comparison to that by a non-adaptive notch filter.

As we have seen in Section 1.2, the EMG signal due to muscular activity may interfere with the ECG signal. The EMG signal seen on the skin surface is quite localized in nature. Due to this property, the EMG interference in different ECG leads may be uncorrelated because the different leads are placed at different locations on the body. With this rationale an adaptive filtering technique has been proposed in [130]. It suggests that for removal of the EMG from one particular lead of the ECG signal which acts as the primary input, the signals from the orthogonal ECG leads can be used as the reference input of the adaptive filter. Thus by using multiple leads of ECG, the EMG interference can be suppressed using this adaptive cancellation technique.

The motion artifact induced due to relative motion of electrodes is more prevalent during ambulatory conditions. It is still a challenging problem to remove motion artifact reliably without affecting the cardiac components of the ECG signal. For reduction of motion artifact, an adaptive recurrent filter (ARF) [130] is suggested that uses the repetitions of the cardiac cycle. Here a cardiac cycle of a fixed length is estimated by the proposed ARF. The ARF coefficients are adapted once in every cycle of ECG so that the impulse response of the filter represents the P-QRS-T complex of the fixed length. Here the estimate of the fixed length of the P-QRS-T complex may leave some temporal gap between the two cycles which can be filled in by using a linear interpolation of the two end points of the gap. The ARF is modified in [105], to have a variable length filter according to the current RR interval so that the filter itself can handle variable heart rates without leaving any gaps. In another approach for removal of motion artifact, in [73], a signal across two extra electrodes placed near right biceps muscle with a separation of 5mm, is used as the reference input whereas the composite ECG signal is the primary input of the adaptive filter. In [73], a recursive least squares (RLS) adaptation is considered to be more suitable than the least mean squares (LMS) algorithm for faster convergence. In [40], it is shown that an impedance variation due to electrode deformation, measured across two electrodes using an ac current, can be used as a reference signal for an adaptive filter for the removal of the motion artifact. It is also reported that the variations in the impedance due to skin/electrode stretching are captured better when the reference signal frequency is 120Hz. The sensitivity of the impedance signal toward electrode deformation drops with increasing frequency of the supplied current. In [40], it has also been shown that the signal acquired from an optical sensor placed at the electrode site can represent the deformation in shape of electrode due to motion and hence can be used for removal of motion artifact. A method of deriving a reference signal using a magneto-resistive sensor and a 3-axes accelerometer for adaptive filtering of motion artifact are proposed in [131].

Apart from adaptive filtering, there are several other techniques used for calculating an estimate of the cardiac cycle by suppressing the noise. In [5], several ECG beat epochs are used in alignment to find an estimate of ECG beat using arithmetic mean, median, a hybrid of both mean and median, trimmed mean, and fixed incremental based methods. In [5], a filter bank approach is also proposed for processing of ECG signal in subbands, utilizing the spectral and temporal properties of the cardiac cycle.

2.5 Detection of Body Posture Changes

Body position changes (BPC) cause angular shifts in the axis of the heart which may result in suppression or elevation of ST segment of the cardiac cycle [53]. These changes in the level of the ST segments due to BPC might be falsely interpreted as ischemia, a cardiac disorder which is characterized by transient changes in ST segment. In order to prevent this kind of false alarms in ischemia monitoring, researchers have tried to detect the BPC from the ECG signal itself. In [49], a method for detecting BPC is proposed based on the fact that BPCs are abrupt and cause step like changes in the ST level. In order to detect a step like change in ST signal three measures are defined for the flatness at a given point: average of a fixed number of samples prior to the given point, called backward region, average of a fixed number of samples after the given point, called forward region and difference between the averages of the forward and backward regions. A step like behavior is determined by appropriate thresholds on these three measures.

In [50, 51, 52], the BPCs are detected by showing that BPC affects both the QRS and ST segments abruptly whereas during ischemia episodes mainly the ST segment is affected gradually. Karhunen-Loeve transform (KLT) coefficients are used to demonstrate this and for detecting this characteristic difference between ischemic and BPC related changes in ST segment. The area under QRS [57] and the width of R wave [115] have also been used to characterize BPC.

In [37], BPC is detected using a Bayesian approach with two conditional probability density functions for the observations in three orthogonal vectorcardiographic leads. The observations can be KLT coefficients for QRS and ST segments or rotation angles derived from the vectorcardiographic leads.

2.6 Overview of Wearable ECG Recorders

Ambulatory ECG recording technology has continuously evolved and matured over time. Originally, Holter had proposed a wearable system that would record the ECG signal in analog form and transmit the recorded ECG signal using a wireless link. This type of system was proposed for ambulatory applications [26, 44, 45].

The state-of-the-art W-ECG recorders are very light weight (< 80gms) and portable, can record long term ECG signal in digital form with a variety of (or programmable) sampling rates as high as 1kHz. Many of them are equipped with wireless transceivers, microprocessors with on board analysis algorithms for calculating cardiac parameters and displaying them on LCD displays and also generating warnings for clinical attention, if necessary. This is made possible due to miniaturization of electronics components, customized chip design for specific analog processing, availability of high speed microcomputers and ECG analysis algorithms [47, 113, 117, 134]. We provide the hardware details of one such W-ECG in the next chapter.

W-ECG uses pre-defined ECG leads which are to be connected to the ECG electrodes appropriately placed on the body. In the standard 12-lead ECG the primary leads are connected to the limbs and hence also referred as limb leads. However, in ambulatory applications the limb leads may obstruct the usual activities of the user (wearer) and hence a modified placement of electrodes is used, called proximal limb leads. In the proximal limb leads the electrode placements are on frontal trunk approximating the positions on the limb sites in the standard ECG [12].

For wearable applications the type of ECG electrodes should be easy to use, compact in size and be able to provide reliable connection for a long duration. Disposable foam-pad adhesive Ag/AgCl electrodes fulfill all such requirements of W-ECG and hence they are preferred in W-ECG. Previously, a large number of studies have focused on electrodes and impact of their placement on ECG applications. In order to reduce the number of electrodes, feasibility of ground-free ECG recording with two electrodes has been investigated in [125].

Skin preparation prior to ECG recording is a standard practice in hospitals in order to reduce the artifacts. This involves removal of hair from the electrode sites, scrubbing of the sites with alcohol (spirit) wipes, and abrasion with abrasive pads. This can help for a short term (for a few minutes) monitoring. However, it has been concluded from the studies carried out on effect of skin preparations on generation of motion artifacts in [126] that the skin preparations are not very helpful for reducing the motion artifact in long term monitoring. Thus the motion artifact cannot be easily prevented and it is a serious problem in a long term monitoring using W-ECG.

2.7 Analysis of Ambulation in ECG

In Section 2.5, we have noted how BPC during sleep may affect the ECG signal. In ambulatory conditions the ECG signal manifests many abnormal and abrupt changes due to motion artifact caused by body movement activities (BMA) of the subject. To interpret the ECG signal correctly in ambulatory conditions, efforts are made to characterize and eliminate the motion artifact signal from ECG.

In [86], a wearable system that can simultaneously record the ECG signal and 2-axes acceleration is developed. The heart rate and the activity levels are compared. The system could not detect the heart rate correctly due to motion artifacts at activity levels which exhibited high acceleration values. From this work it can be concluded that the level of activity in terms of acceleration determines the quality of the ECG captured.

Another such system for recording ECG and 2-axes acceleration signal has been developed in [145]. The heart rate, respiratory rhythm, postural behavior and activity of the subject are computed from the recorded signals. The study reveals that the RR interval, respiration, posture, behavior and activity are very much inter-dependent. Therefore, the information regarding various activities undertaken by the subject must also be used in the ambulatory cardiovascular analysis.

A prototype for wearable ECG monitoring system capable of recording and transmitting continuous ECG and accelerometer data is presented in [43]. Here it is reported that the algorithm used for computing the heart rate from the captured ECG becomes inaccurate at high activity levels as measured by the accelerometer. Thus the measurement of acceleration should be considered while considering the reliability of the estimate of heart rate reported by the automated algorithm.

In [17], a study is performed on the use of wearable devices for monitoring the patient movement. From analysis of simultaneous traces of ECG and acceleration signals shown in [17], we conclude that the motion artifacts are generated in the ECG signal when there is an abrupt and significant change in the acceleration signal due to patient ambulation.

Though the above studies have not quantitatively reported the impact of the levels of the body movement on the generation of motion artifacts in the ECG signal in ambulatory conditions, a reasonable conclusion is that the amount of motion artifact should be proportional to the level of the BMA in terms of body accelerations. We discuss this issue as one of the main topics in this monograph.

Apart from the above works related to the ambulation studies in ECG, a BMA specific characterization of motion artifacts has been proposed using a wavelet transform and a neural network [92, 93]. The signatures of three typical movement patterns are extracted by characterizing the low frequency artifacts from the ECG signal itself. However, the reported performance is not very satisfactory as the wavelet based representation does not separate the in-band BMA signal from the ECG.

We have seen in this review that many useful and accurate algorithms are available in the literature for automated analysis of ECG signal. However, they fail under subject ambulation due to the contamination of the ambulatory ECG signal by the motion artifacts. The context of ambulation can be useful in interpretation of automated analysis of the signal in W-ECG. However, there is no standard reference database of ECG with ambulation information available for carrying out the studies on impact of BMA on the ambulatory ECG signals. In the remaining chapters of the monograph we will focus on the W-ECG and the analysis of the ambulatory ECG signal. We will perform some experiments on using motion artifacts in ambulatory ECG signal as a source of information, while encountering the real life situation, when the wearer is performing all kinds of daily activities like walking, climbing stairs, etc. In the next chapter we provide some of the hardware details and useful specifications of the W-ECG used for this work.

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